ON S011. MOISTURE RETRIEVAL AND TARGET DECOMPOSITION

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1. INTRODUC'1'10N

in an earlier study, an empirical model was developed to infer soil moisture and surface roughness from radar data [1]. The inversion technique was extensively tested over bare surfaces by comparing the estimated soil moisture to *in situ* measurements. The overall R MS error in the soil moisture estimate was found to be 3.5 % and the RMS error in the RMS height estimate was less than 0.35 cm absolute for bare or slightly vegetated surfaces. However, inversion results indicate that significant amounts of vegetation cause the algorithm to underestimate soil moisture and overestimate RMS height. Among the areas over which the inversion cannot be applied, the areas with intermediate vegetation cover are of particular interest as both the vegetation and the underlying bare surface affect the backscatter. This paper concentrates mostly on these areas. Using the full polarimetric information and the Cloude target decomposition approach [2], three different components of the target backscattering can be isolated. One of these three components can be identified as the surface component in the case of intermediate vegetation cover. Once the surface component of the scattering is isolated, the bare surface inversion can then be applied.

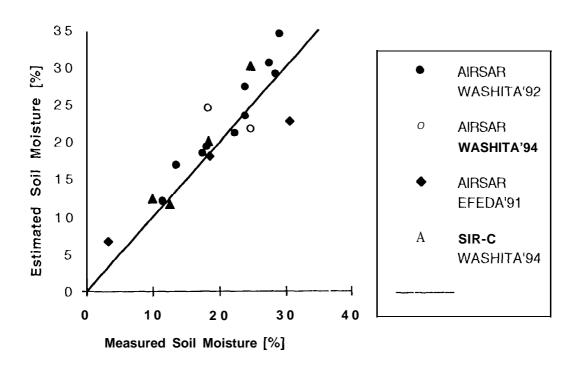
2. SOIL MOISTURE RETRIEVAL, FOR BARESURFACES

The soil moisture retrieval method presented in [1] relies on the two following equations describing the hh-polarized and vv-polarized backscattering coefficients σ_{hh}^o and σ_{vv}^o as a function of θ , the incidence angle, ε , the real part of the dielectric constant, h, the Root Mean square (RMS) height of the surface, k, the wave number and λ , the wavelength in cm:

$$\sigma_{hh}^{\theta} = 10^{-2.75} \frac{\cos \theta}{\sin \theta}^{1.5} 10^{0.028 \mathcal{E} \tan \theta} (kh \sin \theta)^{1.4} \lambda^{0.7}$$

$$\sigma_{vv}^{\theta} = 10^{-2.35} \frac{\cos \theta}{\sin \theta}^{3} 10^{0.046 \mathcal{E} \tan \theta} (kh \sin \theta)^{1.1} \lambda^{0.7}$$
(1)

The RMS height of the surface and the dielectric constant can easily be inverted from these two relations. Once the dielectric constant is known, the volumetric soil moisture can be computed using the Hallikainen curves [3] or the. Brisco curves [4]. The inversion accuracy was extensively tested over a variety of sensors and sites as described in Figure 1. The overall RMS errors were found to be less than 0.4 cm in RMS height and 3.5% in soil moisture. The algorithm is optimized for bare surfaces and requires two co-polarized channels at a frequency between J.5 GHz and 1 J GHz. It gives best results for $kh \le 2.5$, $\mu_x \le 35\%$, anti 0230°.



1 figure 1: Radar derived soil moisture versus in situmeasurements.

Omitting the usually weaker by-polarized returns makes the algorithm Icss sensitive to system cross-talk and system noise, simplifies the calibration process and adds robustness to the algorithm in the presence of vegetation. 1 lowever, inversion results indicate that significant amounts of vegetation (NDVI > 0.4) cause the algorithm to underestimate soil moisture and overest i mat c RMS height. A simple criterion based on the $\sigma_{hv}^0/\sigma_{vv}^0$ ratio was developed to select the areas where the inversion is not impaired by the vegetation. 1 n the following paragraphs, we will present a way to estimate the soil moisture for surfaces with intermediate vegetation cover.

3. Cl .01)1)11 I)I₁XX)MI'OSI'J¹ION

Cloude showed that a general covariance matrix [7'] can be decomposed as follows:

$$[T] = \lambda_1 \bar{k}_1 \bullet \bar{k}_1^{\dagger} + \lambda_2 \bar{k}_2 \bullet \bar{k}_2^{\dagger} + \lambda_3 \bar{k}_3 \bullet \bar{k}_3^{\dagger} + \lambda_4 \bar{k}_4 \bullet \bar{k}_4^{\dagger}$$
 (2)

In (2), λ_i , i=1,2,3,4 are the eigenvalues of the covariance matrix, \bar{k}_i , i=1,2,3,4 are the eigenvectors of [T], and \bar{k}_i^{\dagger} means the *adjoint* (complex conjugate transposed) of \bar{k}_i . in the monostatic case, for reciprocal media, the covariance matrix has one zero eigenvalue and the decomposition results in at most three covariance matrices on the right-lumd side of (2).

Also useful in our discussions later is Cloude's definition of target entropy,

$$H_T = \sum_{i=1}^{4} -P_i \log_4(P_i) \quad \text{where} \quad P_i = -\frac{\lambda_i}{4} - \sum_{j=1,4} \lambda_j$$
 (3)

As pointed out by Cloude, the target entropy is a measure of target disorder, with $H_7 = 1$ for random targets and $H_1 = 0$ for simple (single) targets.

The covariance matrix for azimuthally symmetrical natural terrain in the monostatic case was shown [5] to follow the general form:

$$[T] = c \begin{pmatrix} 1 & 0 & \rho \\ 0 & \eta & 0 \\ \rho^* & 0 & \zeta \end{pmatrix} \text{ where }$$

$$c = \frac{\langle S_{hh}}{\langle S_{hh} \rangle} \frac{\langle S_{hh}}{\langle S_{hh} \rangle} \frac{\langle S_{hh}}{\langle vv} \rangle \eta = \frac{2\langle S_{hv} S_{hv}^* \rangle}{\langle S_{hh} S_{hh}^* \rangle} \text{ and } \zeta = \frac{\langle S_{vv} S_{vv}^* \rangle}{\langle S_{hh} S_{hh}^* \rangle}$$
(5)

$$c = \frac{\langle S_{hh}}{S_{hh}^*} \frac{\langle S_{hh}}{\langle S_{hh}, S_{hh}^* \rangle_{vvi}^* \rangle} \eta = \frac{2 \langle S_{hv}, S_{hv}^* \rangle}{\langle S_{hh}, S_{hh}^* \rangle} \text{ and } \zeta = \frac{\langle S_{vv}, S_{vv}^* \rangle}{\langle S_{hh}, S_{hh}^* \rangle}$$
(5)

The superscript *means complex conjugate, and all quantities are ensemble averages. The parameters c, ζ , ρ and η all depend cm the sire, shape and electrical properties of the scatterers, as well as their statistical angular distribution. It is easily shown that the eigenvalues of [T] are [6]

$$\lambda_1 = \frac{c}{2} \left(\zeta + 1 + \sqrt{(\zeta - 1)^2 + 4\rho \rho^*} \right) \tag{6}$$

$$\lambda_2 = \frac{c}{2} \left(\zeta + 1 - \sqrt{(\zeta - 1)^2 + 4\rho \rho^*} \right) \tag{7}$$

$$\lambda_3 = c\eta \tag{8}$$

Because T is a Hermitian matrix, the three eigenvalues are real and greater than zero

'I'he corresponding three eigenvectors are

$$\bar{k}_{1} = \sqrt{\frac{\left(\zeta - 1 + \sqrt{\Lambda}\right)^{2}}{\left(\zeta - 1 + \sqrt{\Lambda}\right)^{2} + 4\rho\rho^{2}}} \begin{pmatrix} 2\rho \\ \left(\sqrt{\Lambda} + (\zeta - 1)\right) \\ 0 \\ 1 \end{pmatrix}$$
(9)

$$\widetilde{k}_{2} = \sqrt{\frac{\left(\zeta - 1 - \sqrt{\Delta}\right)^{2}}{\left(\zeta - 1 - \sqrt{\Delta}\right)^{2} + 4\rho\rho^{*}}} \qquad \overline{\left(\sqrt{\Delta} - (\zeta - 1)\right)} \qquad (10)$$

$$\bar{k}_3 = \begin{pmatrix} \mathbf{0} \\ 1 \\ 0 \end{pmatrix} \tag{11}$$

where

$$\Delta = (\zeta - 1)^2 + 4\rho \rho^*. \tag{12}$$

The square root terms in front of the eigenvectors in (9-10) are them for normalization purposes and are always positive. We note that A is positive and that $\sqrt{\Lambda}$ is always greater than $|\zeta - 1|$. Also note that WC can write

$$\frac{k_{11}}{k_{21}} = -D \frac{\left(\sqrt{\Delta - (\zeta - 1)}\right)}{\left(\sqrt{\Delta + (\zeta - 1)}\right)} \tag{13}$$

where Dincludes the square-root factors in front of the vectors in (9, 10) and is therefore always positive. It is easy to see then that the ratio in (13) is always real and negative. This means that the first two eigenvectors represent scattering matrices that can be interpreted in terms of odd and even numbers of reflections when $A rg(\rho)$ is close to zero. This is the case for scattering dominated by the surface scattering term.

4. S011, MOISTURE RETRIEVAL FOR INTERMEDIATE VEGETATION COVER

When surface scattering dominates, these conditions given by van Zyl [7] are met:

$$\operatorname{Re}(\rho) \ge \frac{\eta}{2}$$
, $\frac{\eta}{2} \le 1$ and $\operatorname{Arg}(\rho) \approx 0$ (14)

The first eigenvalue, λ_1 corresponds then to the surface scattering term as k_p , is positive. It was pointed out in [1] that the presence of vegetation causes the inversion to underestimate the soil moisture and overestimate the roughness, in the following paragraph, we show that applying the inversion on the cross-sections corresponding to the first eigenvalue corrects this tendency by resulting in a higher soil moisture and a lower RMS height estimate than the straightforward inversion on the cross-sections corresponding to the original covariance matrix.

From (14), we know that ρ is a positive real. We can then write (9) and (1 0) as:

$$\bar{k}_1 = \frac{1}{A} \begin{pmatrix} \alpha \\ 0 \\ 1 \end{pmatrix}, \ \bar{k}_2 = \frac{1}{B} \begin{pmatrix} -\beta \\ 0 \\ 1 \end{pmatrix} \text{ and } \ \bar{k}_3 = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix}$$
(15)

where

$$\alpha = \frac{2\rho}{\sqrt{\Lambda + (\zeta - 1)}} \text{ and } \beta = \frac{2\rho}{\sqrt{\Lambda - (\zeta - 1)}}$$
 (16)

A, B, α and β are real and positive.

The original covariance matrix and the 1111 to VV ratio can be written as:

$$[T] = \begin{pmatrix} \frac{\lambda_1}{A^2} \alpha^2 + \frac{\lambda_2}{B^2} \beta^2 & 0 & \frac{\lambda_1}{A^2} \alpha + \frac{\lambda_2}{B^2} \beta \\ 0 & \lambda_3 & 0 \\ \frac{\lambda_1}{A^2} \alpha + \frac{\lambda_2}{B^2} \beta & 0 & \frac{\lambda_1}{A^2} + \frac{\lambda_2}{B^2} \end{pmatrix}$$
(17)

$$\frac{\sigma_{hh}^{0}}{\sigma_{vv}^{0}} = \frac{\frac{\lambda_{1}}{A^{2}}\alpha^{2} + \frac{\lambda_{2}}{B^{2}}\beta^{2}}{\frac{\lambda_{1}}{A^{2}} + \frac{\lambda_{2}}{B^{2}}} = \alpha^{2} + \frac{\frac{\lambda_{2}}{B^{2}}(\beta^{2} - \alpha^{2})}{\frac{\lambda_{1}}{A^{2}} + \frac{\lambda_{2}}{B^{2}}}$$
(18)

The covariance matrix corresponding to the first eigenvalue is:

$$[T]_{l} = \begin{pmatrix} \frac{\lambda_{1}}{A^{2}} \frac{\alpha^{2} 00 - \frac{\lambda_{1}}{A^{2} l^{2}} \alpha}{A^{2} A^{2} & A^{2} l^{2} \alpha} \\ 0 & 0 & 0 & 0 \\ \frac{\lambda_{1}}{A^{2}} \alpha & 0 & \frac{\lambda_{1}}{A^{2}} \end{pmatrix} \text{ and } \frac{\sigma_{hh}^{o}}{\sigma_{vi}^{o}} = \alpha^{2}$$

$$(19)$$

As long as ζ is greater than 1, $\beta \ge \alpha$ and the 111110 VV ratio of the full covariance matrix is β 1211"gcl'(C]OSCJ'10 1) than the β 111to VV ratio of sill'files component of the covariance matrix. It follows that the soil moisture estimated from the first component of the decomposition will be higher than the soil moisture estimated from the full covariance matrix. It is also straightforward to see that the σ_{hh}^0 is larger for the original matrix than for the first component, resulting in a lower estimated value of the RMS height in the case of the surface component only.

5. CONCLUDINGREMARKS

This paper describes a method to widen the domain of applicability of a soil moisture inversion algorithm previous] y published to include areas of intermediate veget at ion cover. This method was tested on AIRSAR and S11<--. images and the results will be presented during the Workshop. In particular the following points will be clarified.

The method applies to surfaces with an azimuthal symmetry, with $\frac{\sigma_{hh}^o}{\sigma_{vv}^o} \le 1$ and $Arg\langle S_{hh}S_{vv}^* \rangle \approx 0$.

We will show that these conditions are met by most natural surfaces.

In [1], the authors introduce the 1 IV to VV ratio as a vegetation detector, We will evaluate how this criterion can be interpreted in the light of the Cloude decomposition and analyze the value of the decomposition step by identifying those surfaces rejected under the 1 IV to VV ratio criterion for which the decomposition method allows an estimation of the soil moisture.

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